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NPS and Online WOM: Investigating the Relationship Between Customers' Promoter Scores and eWOM Behavior

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Abstract

The Net Promoter Score (NPS) is, according to Reichheld, the single most reliable indicator of company growth, and many companies use this recommendation-based technique for measuring customer loyalty. Despite its widespread adoption by many companies across multiple industries, the debate about NPS goes on. A major concern is that managers treat NPS as being equivalent across customers, which is often very misleading. By using a unique data set that combines customers' promoter scores and online word-of-mouth (eWOM) behavior, this research studies how individual customers' promoter scores are related to eWOM, including its relationship with the three categories of customers that are identified by the NPS paradigm (i.e., promoters, passives, and detractors). Based on a sample of 189 customers, their promoter scores and corresponding eWOM, the results show that there is a positive relationship between customers' promoter scores and the valence of online messages. Further, while detractors and promoters are homogeneous with respect to the valence of the eWOM messages they spread, passives show message valence heterogeneity. Thus, although passives, the largest group of customers, have no weight in calculating the NPS, our results reveal that companies should flag passives for further attention and action.

Keywords

Net Promoter Score (NPS), online word of mouth, eWOM

Since the introduction of the net promoter concept by Reichheld (2003), the Net Promoter Score (NPS) has become an increasingly popular method for measuring customer loyalty. The NPS assesses to what extent a customer would recommend a certain company to friends or colleagues. Due to its simplicity and ease of measurement, many companies within different industries have adopted the NPS as *the* corporate metric (Gupta and Zeithaml 2006). Indeed, companies such as Apple, Intuit, and Philips have put NPS at the center of their management processes (Forbes 2011; Reichheld and Markey 2011). The growing importance of word-of-mouth (WOM) communications has made the NPS even more attractive. Despite its popularity, the majority of companies using NPS struggle with implementing it successfully. According to Forrester analyst Harley Manning (as cited by Bulik 2013), "No metric has more awareness than Net Promoter Scores. But among people who use it, not many use it particularly well."

One of the reasons why companies fail to implement NPS successfully is that managers treat promoter scores as being equivalent across customers.¹ Indeed, Reichheld (2003) suggests that, by basing customers' responses on a 0–10 rating scale, customers can be classified as "promoters" (those providing promoter scores of 9 or 10), "passively satisfied" (respondents giving scores of 7 or 8), or "detractors" (those giving scores of 0 to 6). Treating these groups as being homogeneous suffers from ecological fallacy (Keiningham et al.

2014), that is, drawing conclusions about individual customers based on analyses of group data, which makes it hard to detect differences between individual customers' promoter scores. This might be problematic for two reasons. First, it is suggested that the NPS is an attitudinal measure of intention to recommend rather than a measurement tool for actual WOM behavior (East, Hammond, and Lomax 2008). Indeed, what people say, what people do, and what they say they do might be different things (Chandon, Morwitz, and Reinartz 2005; Sheeran 2002). Thus, only a portion of the customers who state that they will recommend the company to others actually do so (Kumar, Petersen, and Leone 2007), rendering information on how individual customers' promoter scores relate to actual WOM behavior relevant. Second, data loss is considered as a major flaw of the net promoter concept (East, Hammond, and Lomax 2008; Kristensen and Eskildsen 2014). For example, the NPS disregards differences between a score of 0 and 6, which both reflect the detractor category. It could be expected, however, that

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customers who are not willing to recommend the company to friends or colleagues are different from customers who are indifferent about their willingness to recommend. If this holds true, managers get more information if they use the entire distribution of promoter scores instead of a one number summary statistic.

Against this backdrop, the goal of this study is 2-fold. First, we empirically test the relationship between customers' promoter scores (i.e., measure of intention to recommend the company to friends or colleagues) and their actual WOM behavior (i.e., message valence, recency, and frequency). Second, based on the individual customers' responses to the promoter question, we examine whether customers assigned to the same (different) NPS category are homogeneous (heterogeneous) with respect to WOM message valence. We do so by examining a unique data set that combines customers' promoter scores and their eWOM behavior. The results show that customers who provide high (low) promoter scores are more likely to spread positive (negative) eWOM. Further, this positive relationship is stronger for customers who spread more compared to less eWOM messages. In addition, the findings reveal that promoters and detractors are homogeneous concerning eWOM message valence. On the contrary, passively satisfied customers are heterogeneous if eWOM message valence is considered.

The remainder of this study is organized as follows. Literature on the NPS and its relationship to loyalty and WOM is first reviewed, and the objectives of our study are defined. The method is then described, and the results are presented. In the final section, implications are discussed and suggestions for further research are provided.

Theoretical Background

The NPS Concept, Loyalty, and WOM

The NPS is based on a single loyalty question: "How likely is it that you would recommend our company to a friend or colleague?" Based on the customers' individual promoter scores, customers can be classified as promoters, passives, or detractors (Reichheld 2003). Promoters are extremely likely to recommend the company to others. In contrast, detractors are extremely unlikely to make recommendations and are responsible for 80% to 90% of a company's negative WOM (Reichheld 2006). The detractors' complaints to their friends and colleagues about a company cause damage to a company's reputation and undermine sales and growth (Reichheld 2003, 2006). An NPS is the percentage of promoters minus the percentage of detractors. Reichheld (2003, p. 54) claims that the NPS is the one number you need to grow. While academics and market researchers debate this statement (e.g., Keiningham et al. 2007, 2008a; Morgan and Rego 2006; Van Doorn, Leeflang, and Tijs 2013), many companies have adopted the NPS, proving the importance attributed to WOM (as an alternative measure of loyalty) as a crucial value driver (Beckers, Risselada, and Verhoef 2014; Kumar, Pozza, and Ganesh 2013, p. 251).

The consensus is that WOM can have a major impact on consumers' responses to a product (Keiningham et al. 2007), affecting the majority of all purchase decisions (East, Hammond, and Lomax 2008; East, Hammond, and Wright 2007; Hennig-Thurau et al. 2004; Kozinets et al. 2010; Van Noort and Willemsen 2012). Many companies have chosen to deflect more traditional marketing approaches in favor of WOM (Keiningham et al. 2008b; Trusov, Bucklin, and Pauwels 2009), due to its low costs, interactivity, speed, and lack of commercial bias or higher sense of credibility (East, Hammond, and Wright 2007; Keiningham et al. 2008b; Kozinets et al. 2010; Trusov, Bucklin, and Pauwels 2009). As Trusov, Bucklin, and Pauwels (2009, p. 90) point out, "word-of-mouth marketing is a particularly prominent feature on the Internet." eWOM is defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al. 2004, p. 39). Whereas the influence of traditional, off-line WOM is limited to a local social network and diminishes quickly over time and distance, the impact of eWOM, which is fast, convenient, and available for an indefinite period of time, can reach far beyond the local community (Chen and Xie 2008; Dellarocas 2003; Duan, Gu, and Whinston 2008). This makes companies more dependent than ever on cultivating positive WOM and eliminating negative WOM (de Matos and Rossi 2008; Reichheld 2006).

In sum, it is known that WOM plays a role in consumer decision-making and purchase behavior (Kumar, Petersen, and Leone 2010), and with the arrival of interactive and social media, eWOM is rapidly becoming more prevalent (Chen and Xie 2008; Duan, Gu, and Whinston 2008). At the same time, practitioners widely embrace and adopt WOM-based strategies such as the NPS (Keiningham et al. 2007; Luo 2009). However, the relationship between NPS and eWOM has received little attention, an issue that is taken up in this research. In particular, this study examines how individual customers' promoter scores are related to eWOM behavior. The primary focus is on customers' promoter scores rather than the NPS to avoid falling in the ecological fallacy trap.

Research Objectives

The purpose of this study is 2-fold. Firstly, whether customers' promoter scores (i.e., intention to recommend) represent actual eWOM behavior (i.e., spreading positive, neutral, or negative messages) will be examined. Secondly, by making use of the full scale (i.e., the 0 to 10 scale), it will be investigated whether customers who are assigned to the same NPS category (i.e., promoters, passives, or detractors) are homogeneous regarding the valence of their eWOM messages but differ in message valence from customers assigned to the other categories.

Customers' promoter scores and eWOM behavior. Rust, Zeithaml, and Lemon (2000, p. 46) observe that the effect of WOM is frequently significantly large, but at the same time notoriously

hard to measure. The nearest that most companies get to estimating the value of a customer's WOM referral power is some gauge of the customer's likelihood or intention to recommend the company (Kumar, Petersen, and Leone 2007). It is well known, however, that measures of behavioral intentions are at best imperfect representations of actual behavior (Brown et al. 2005, p. 129; Chandon, Morwitz, and Reinartz 2005; Sheeran 2002). In particular, stated intentions substantially overstate actual behavior, especially in a WOM context (de Matos and Rossi 2008).

Based on this line of reasoning, one might question whether the "would recommend" question is able to capture actual customer behavior. In other words, will customers who provide companies with high (low) promoter scores engage in positive (negative) eWOM behavior? More generally, is an individual customer's promoter score consistent with this customer's eWOM message valence? To answer these questions, individual customers' promoter scores are related to the content of these customers' eWOM messages (i.e., positive, neutral, or negative valence).²

In addition to content, customers control the timing and frequency of their messages. With regard to timing, it is expected that the closer the date of the online message to the date of the NPS survey (i.e., recency), the stronger the relationship between customers' promoter scores and eWOM message valence. Indeed, those who have scored a company most recently have more vivid, novel, or memorable experiences about the company or its products and services and are more likely to share their experiences via eWOM (cf. Duan, Gu, and Whinston 2008). Frequency refers to how often customers engage in eWOM about the company (Harrison-Walker 2001). Previous literature indicates that customers give more positive than negative WOM (East, Hammond, and Wright 2007). We expect therefore that the positive relationship between customers' promoter scores and eWOM message valence is stronger for customers who spread online messages more frequently compared to customers who show a lower eWOM activity. To empirically examine these assertions about recency and frequency, these variables and their interactions with the customers' promoter scores will be added to our model.

Message valence homogeneity within and heterogeneity across NPS categories. One of the most attractive features of the NPS is its simplicity (Keiningham et al. 2008a). The core idea that the more promoters and the fewer detractors a company has, the bigger its growth (Reichheld 2003) is appealing to corporate managers. Its simplicity, however, could also be considered as a major weakness. The net promoter concept classifies customers into three categories, that is, promoters, passives, and detractors. These categories are then treated as being homogeneous (Keiningham et al. 2014). Assuming homogeneity within categories might be problematic because the NPS does not measure negative WOM. Rather, negative WOM is inferred from low-positive WOM (East, Hammond, and Lomax 2008). Consequently, it may be incorrect to assume that

detractors engage in negative WOM behavior as individual differences may arise. In particular, customers who indicate an unlikeliness to recommend the company to a friend or colleague (those providing the company a promoter score of 0) may be more likely to spread negative WOM than customers giving a score of 5 or 6. While this latter group of customers might give less positive eWOM than customers classified as passives or promoters, it is questionable if this group of customers will actually engage in negative eWOM.

Thus, one might argue that the "one-size-fits-all" feature of the NPS makes it impossible to detect differences between customers' individual promoter scores (Keiningham et al. 2014) and does not allow for variation in the impact of WOM across customers within categories. To examine whether customers differ in their eWOM message valence, this study will use the full scale (i.e., the 0 to 10 scale) rather than assigning customers to categories and focusing on the extremes (i.e., promoters and detractors) and can therefore be perceived as a test to justify the classification into promoters, passively satisfied customers, and detractors.

Method

Empirical Context

A unique data set that combines customers' promoter scores and their eWOM behavior was used to test the research questions. The particular context of eWOM behavior was selected for several reasons. Firstly, company interest in WOM behavior has increased exponentially mainly due to the NPS (Rana-weera and Jayawardhena 2014), and increasingly these recommendations are made on social media (Mackintosh 2015). Each day, 1.4 billion Facebook users share about 2.2 billion pieces of content worldwide, YouTube attracts more than 30 million unique users, an average of 58 million photos are uploaded to Instagram, and customers send 58 million tweets via Twitter (StatisticBrain.com 2015). Secondly, to obtain unbiased measures, actual WOM behavior should be observed (East, Hammond, and Wright 2007). eWOM behavior allows us to keep track of customers' WOM communications as it occurs. The Internet provides different venues for consumers, such as weblogs, review sites, discussion forums, and social network sites, to share opinions, preferences, or experiences with others (Hennig-Thurau et al. 2004; Trusov, Bucklin, and Pauwels 2009). Thirdly, the exponential growth of social networks has resulted in a rapid increase in the impact of eWOM on decision-making and consequently may become more effective for companies than traditional media and offline WOM (Dellarocas 2003; Trusov, Bucklin, and Pauwels 2009). Indeed, eWOM is playing an increasingly important role in consumers' purchase decisions (Chen and Xie 2008; Duan, Gu, and Whinston 2008).

Data and Sample

Two companies that use the NPS as one of their key indicators of company success participated in our research. The first

company is active in the automotive industry (Company 1), while the other company is a large telecommunication company (Company 2). Both companies provided their customers' promoter scores between 2011 and 2013, including the date of the NPS survey and the corresponding e-mail addresses.

By using these e-mail addresses, it was possible to generate a unique data set that combines customers' promoter scores and their eWOM behavior. In particular, in cooperation with a specialized company, individual customers' promoter scores were matched with messages on their social media accounts (e.g., Facebook, Twitter, and review sites). Note that we used the customer e-mail databases of the participating companies. If customers use multiple e-mail addresses, for example, one e-mail address registered at the company and another e-mail address for social media purposes, we were unable to match the promoter score and eWOM behavior. As a result, these customers are disregarded. To ensure the anonymity of the companies' customers, the e-mail addresses as well as the social media account names were deleted after the matching procedure.

Only messages that were spread within 1 year of the NPS survey date are taken into account. By filtering the social media messages by both author and subject, irrelevant cases were eliminated from the study. Filtering by author allowed only the inclusion of customers that participated in the NPS survey. Filtering by subject selects messages pertaining to one of the two companies participating in the research. Only the messages containing either the company brand names or one of the major company-specific products were maintained. This procedure resulted in a data set consisting of 659 unique customers (334 and 325 customers of Companies 1 and 2, respectively) who spread 1,902 online messages (693 and 1,209 online messages for Companies 1 and 2, respectively).

Ideally, a customer would engage in eWOM at the same time the NPS data are collected. In practice, this will not happen. While for some customers, the time lag between the NPS survey date and the occurrence of eWOM is very short, for other customers, this time lag is longer. It can be assumed that the attitude toward a company will be more or less the same over a short period of time but can change over a longer period of time, depending on whether or not a new experience with the company has occurred (Grossman and Till 1998; Keller 1993). As a result, only the first online messages of customers in which the time elapsed between the date of the NPS survey and eWOM occurrence is less than a month are taken into account. This selection rule leads to a final sample of 189 unique customers (105 and 84 customers of Companies 1 and 2, respectively).

Operationalization

eWOM message valence. To examine whether customers' promoter scores represent true promotion behavior and to test whether eWOM message valence is homogeneous within but heterogeneous across the three customer groups identified by Reichheld (2003), the valence of the social media messages is required, for which a sentiment analysis is necessary. The main

Table 1. Examples of Positive, Neutral, and Negative Valenced Online Word-of-Mouth (eWOM) Messages.

Valence	Example eWOM Message
Company 1	
Very positive	"Really, those men at Company 1 are heroes, they replaced my battery perfectly."
Positive	"With troubles next to the highway . . . Luckily we have Company 1!"
Neutral	"I also have Company 1 on Twitter."
Negative	"Waiting for Company 1 . . . It takes long."
Very negative	"I am waiting for three hours. What a very fast service of company 1, NOT!!!! Do I have to pay my contribution fee for this? Idiots."
Company 2	
Very positive	"Nice, superfast Internet of Company 2 within 10 minutes installed! Top!!!"
Positive	"As of today Company 2 has raised its speed to 40Mbps!!!"
Neutral	"Will Company 2 broadcast the Top 2000 on the event channel?"
Negative	"I have no telephone connection of Company 2."
Very negative	"For the second time within 14 days a whole day of malfunction. This is unacceptable, what a bunch of *&\$\$ at Company 2!"

goal of a sentiment analysis is to determine the polarity of a written text and consequently to ascertain the valence of the sender's message. We manually determine the valence of all customers' social media messages ($N = 1,902$). In particular, two coders content analyzed the messages to identify whether the eWOM message was negative, neutral, or positive (cf. De Matos and Rossi 2008). Cohen's κ , the metric used to guarantee the interjudge reliability, was sufficiently large (Neuendorf 2002), that is, 98% for Company 1 and 96% for Company 2, respectively. Differences between the coders were reconciled through in-depth discussion between the coders and an independent observer. Table 1 provides examples of (very) positive, (very) negative, and neutral messages provided by the companies' customers.

eWOM message recency and frequency. Recency measures the time elapsed in days between the NPS survey date and the date the customer engaged in eWOM about the company. Frequency refers to the number of online messages spread by a customer during the sampling period. This measurement is log-transformed to reduce skewness. We use mean-centering before forming the interactions to ease interpretation.

Control variable. To remove company-specific effects, a company dummy is included ($0 = \text{Company 1}$; $1 = \text{Company 2}$).

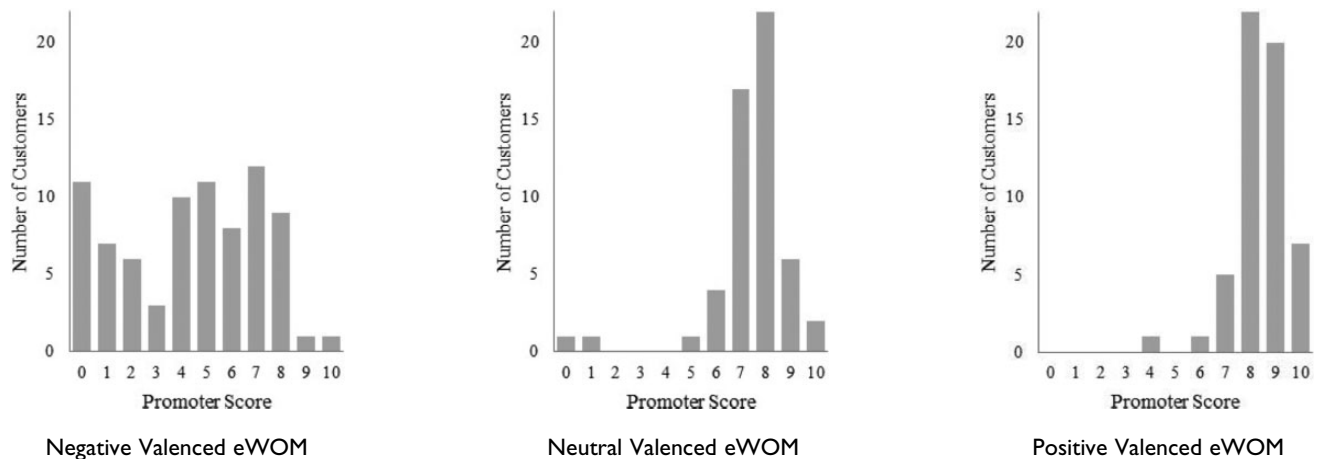
Results

Descriptive Statistics

Table 2 provides descriptive statistics on customers' promoter scores and eWOM message valence. Panel A shows that 34%

Table 2. Descriptive Statistics Customers' Promoter Scores and eWOM Message Valence.**A. Cross-Tabulation NPS Category and eWOM Message Valence**

		eWOM Message Valence			Total
		Negative	Neutral	Positive	
NPS category	Detractors	56	7	2	65
	Passives	21	39	27	87
	Promoters	2	8	27	37
	Total	79 ^a	54	56 ^b	189

B. Distribution Promoter Scores for Negative, Neutral, and Positive eWOM**C. Descriptives Promoter Scores for Negative, Neutral, and Positive eWOM**

Message Valence	Promoter Score Descriptives				
	Average	Standard Deviation	Median	Skewness	Kurtosis
Negative	4.38	2.79	5	-0.20	-1.13
Neutral	7.39	1.68	8	-2.58	9.77
Positive	8.41	1.07	8	-1.26	4.11

Note. $n = 189$. eWOM = online word of mouth; NPS = Net Promoter Score.

^aOf these messages, 29 are coded as very negative. ^bOf these messages, 25 are coded as very positive.

(65 of 189) of the customers is classified as detractors, 46% (87 of 189) are passives, and 20% (37 of 189) are promoters. Further, more than 40% (79 of 189) of the eWOM messages spread by our sample is negative, almost 30% (54 of 189) is neutrally valenced, and about 30% (56 of 189) is positive. Panel B provides more detail by plotting the distribution of customers (per promoter score) that spread negative, neutral, or positive eWOM. The average promoter scores for customers with positive, neutral, and negative message valence (see Panel C) are significantly different ($ps < .01$). As expected, customers with a higher promoter score posted more positively valenced online messages than customers who had a lower promoter score.

Concerning recency, the data show that promoters, on average, engage in eWOM significantly sooner (9.08 days) than passives (12.79 days; $p < .05$; see Figure 1). Detractors fall

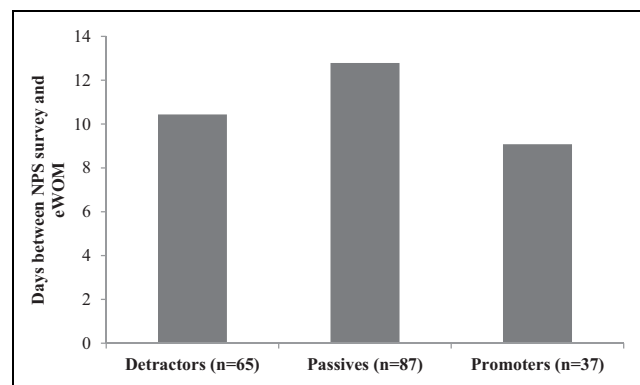


Figure 1. Average number of days between the Net Promoter Score survey date and the date of the online word-of-mouth message for detractors, passives, and promoters ($n = 189$).

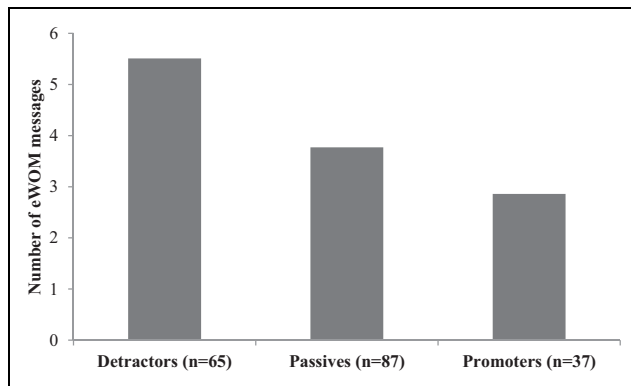


Figure 2. Average number of online word-of-mouth messages spread by detractors, passives, and promoters ($n = 189$).

Table 3. Correlation Matrix.

Variable Name	eWOM Message Valence	Promoter Score	Recency	Frequency	Company Dummy
eWOM message valence	1				
Promoter score	.63	1			
Recency	.05	.06	1		
Frequency	-.18	-.17	-.17	1	
Company dummy	-.27	-.14	.06	.04	1

Note. eWOM = online word of mouth.

in between (10.45 days) and do not significantly differ from promoters and passives regarding the timing of eWOM ($ps > .10$). It should be noted, however, that this category shows great dispersion. Especially, customers who score the company very low (i.e., a promoter score of 0, 1, or 2) are quick to engage in eWOM behavior (on average 8.34 days). Within 1 month our sample of 189 customers spread 405 eWOM messages, of which 208 messages pertain to Company 1 and 197 messages to Company 2. Fifty customers spread multiple eWOM messages (i.e., two or more) with a maximum of 29. We could derive that, on average, detractors show a marginal significantly higher eWOM activity (5.51 online messages) compared to passives (3.77 online messages; $p < .10$) and are significantly more active than promoters (2.86 online messages; $p < .05$; see Figure 2).

Multicollinearity between the variables is not a concern. All correlations among the variables are less than or equal to .63 (see Table 3). Further, variance inflation factors (VIFs) are well below the established threshold of 10 (Gelbrich, Gäthke, and Grégoire 2015), with a maximum VIF of 1.8.

Model Estimation

To address our research questions, we use an ordered logit model because our dependent variable, that is, eWOM message

valence, is an ordinal scale with three levels, that is, positive, neutral, or negative. An ordered logit model estimates the odds of reaching a higher level of the dependent variable (Cummings 2004, p. 358). eWOM message valence is modeled as a function of the individual customers' promoter scores, recency, frequency, and the interactions between customers' promoter scores and recency and frequency. The parameter estimates indicate the log odds of engaging in positively valenced eWOM (vs. the combined neutral and negative eWOM). Table 4 presents the results.

The full model, that is, the model including the interactions with recency and frequency, outperforms an intercept-only model and a model without interactions (Akaike information criterion [AIC] = 300 for the full model compared to AIC = 413 for the model with only an intercept and AIC = 303 for the model without interactions). In addition, the full model has a good explanatory power, as shown by the concordance percentage of 85.1. In contrast to the results of De Haan, Verhoef, and Wiesel (2015), we find that a model including the official NPS (at the customer level, the official NPS takes on a value of -1 for detractors, 0 for passives, and $+1$ for promoters; De Haan, Verhoef, and Wiesel 2015, p. 198) performs less well than a model that focuses on the full-scale variable (i.e., the 0 to 10 scale). With an AIC of 307, model fit is considerably less than our main model that uses the full-scale NPS variable (AIC = 300; Burnham and Anderson 2002). In addition, the explanatory power (concordance percentage) decreases from 85.1 to 82.8 when using a model including the official NPS.

The effect of customers' promoter scores on eWOM message valence is significantly positive ($\beta = 1.04$, $p < .01$). This result indicates that, while the promoter score is a measure of attitude, it is a reasonable proxy for customers' actual eWOM behavior. In addition, we find that the main effect of frequency is negatively significant ($\beta = -1.34$, $p < .05$), indicating that message valence is more negative for customers who spread more messages versus customers who spread less messages. The interaction between customers' promoter scores and frequency is positively significant ($\beta = .74$, $p < .05$). Thus, the positive relationship between customers' promoter scores and eWOM message valence is stronger for customers who show higher eWOM activity compared to those who are less active in spreading online messages.

To address the issue concerning message valence homogeneity within categories, an analysis of variance (ANOVA) is performed, in particular, by comparing the individual promoter scores to examine whether differences regarding eWOM message valence occur. The data reveal that customers who award the company a promoter score of 0 to 6 spread, on average, negative eWOM (see Figure 3). In fact, 86% of detractors engage in negative eWOM, rendering them responsible for more than 70% of the negative eWOM messages in our sample. In contrast, customers who rate the company with a score of 9 or 10 engage, on average, in positive eWOM. About 73% of the promoters spread positive eWOM, and almost half of the positive eWOM messages originate from this group. As expected, most neutral eWOM messages (72%) are spread by passives

Table 4. Results of Ordered Logit Analysis for eWOM Message Valence.^a

Variable	Main Effects Model		Full Model	
	Parameter Estimate	Odds Ratio Estimate	Parameter Estimate	Odd Ratio Estimate
Intercept ^{b,c}				
Cut Point 1	−5.01*** (.93)	.01	−6.14*** (1.21)	.00
Cut Point 2	−6.96*** (1.01)	.00	−8.13*** (1.27)	.00
Main effects				
Promoter score (PS)	0.86*** (.12)	2.36	1.04*** (.17)	2.83
Recency	0.01 (.02)	1.01	.01 (.02)	1.01
Frequency	−0.55** (.32)	.58	−1.34** (.57)	.26
Interaction effects				
PS × Recency			−.01 (.01)	—
PS × Frequency			.74** (.37)	—
Control variable				
Company dummy	−.57* (.32)	.57	−.62* (.33)	.54
−2 Log-Likelihood	291		284	
χ^2 Likelihood ratio	118***		125***	
AIC	303		300	
Concordance percentage	84.9		85.1	
McFadden pseudo R^2	.29		.31	

Note. $n = 189$. eWOM = online word of mouth; AIC = Akaike information criterion.

^aStandard errors are reported in parentheses. ^bThe cut points are like the intercepts in simple linear regressions. An underlying continuous latent variable is used to differentiate the low categories from high categories in the dependent variable (Green, Li, and Nohria 2009). In general, the cut points are not used in the interpretation of the results but are of interest in computing the overall probability of valence level as values of the independent variables increase (cf. Santoro and McGill 2005). ^cCut Point 1 shows the logit for negative versus neutral valence, and Cut Point 2 shows the logit for negative versus positive valence. As we are able to reject the null hypothesis that the cut points are equal ($p < .01$), there seems no need to reduce the number of categories.

* $p < .10$. ** $p < .05$. *** $p < .01$.

(respondents awarding the company marks of 7 or 8). It is, however, noticeable that the majority of passives (55%) engage in either negative or positive eWOM.

Further, the results of the ANOVA, $F(10, 178) = 17.34$, $p < .01$, show that customers rating the company between 0 and 6 (i.e., detractors) do not differ from each other ($ps > .10$) but differ from customers who provide a higher promoter score ($ps < .05$). Additionally, we find that customers rating the company with a score of 9 or 10, that is, the promoters, differ from the other groups of customers ($p < .01$; note that $p < .10$ for the difference between customers rating the company an 8 vs. 10) but are similar to each other ($p = .65$). The difficulty lies with customers, giving the company a promoter score of 7 or 8, that is, passives. It appears that these customers are segments in themselves, as they significantly differ from each other ($p < .01$). This result is reinforced if the predictive accuracy of our ordered logit model is considered. In particular, our model predicts the membership of customers in the negative and positive eWOM valenced groups significantly better than a model that is just based on chance ($ps < .01$). More specifically, the hit rate is 75% and 61% for negative and positive eWOM message valence, respectively. In contrast, while our model also predicts the membership of customers in the neutral valenced group significantly better than random classification would ($p < .05$), the hit rate is only 41%. Collectively, these findings show that Reichheld's (2003) classification of customers into detractors and promoters is justified when online message valence is considered. However, careful attention should

be paid to the group of passively satisfied customers, which is the largest group—they spread 46% of all online messages—and do not appear to be as homogeneous as stated by Reichheld (2003, 2006).

Robustness Checks

To check the robustness of our findings, we perform three additional analyses.

Three-Month, 6-Month, and 1-Year Time Frame

The sample used to estimate our model only includes cases where the time elapsed between the NPS survey date and the occurrence of eWOM is less than a month. Results are validated by examining the relationship between customers' promoter scores and eWOM message valence using 3-month ($n = 335$; 752 messages), 6-month ($n = 478$; 1,132 messages), and 1-year ($N = 659$; 1,902 messages) time lags between the NPS survey date and the occurrence of eWOM. Table 5 presents the results that are robust for these alternative time frames. Specifically, the positive and significant main effect of customers' promoter scores on eWOM message valence ($ps < .01$) and the interaction with frequency ($ps < .10$) are replicated. In contrast to our main findings, the interaction effect between customers' promoter scores and recency is negatively significant for these longer time frames ($ps < .05$). Thus, the positive relationship between promoter score and eWOM

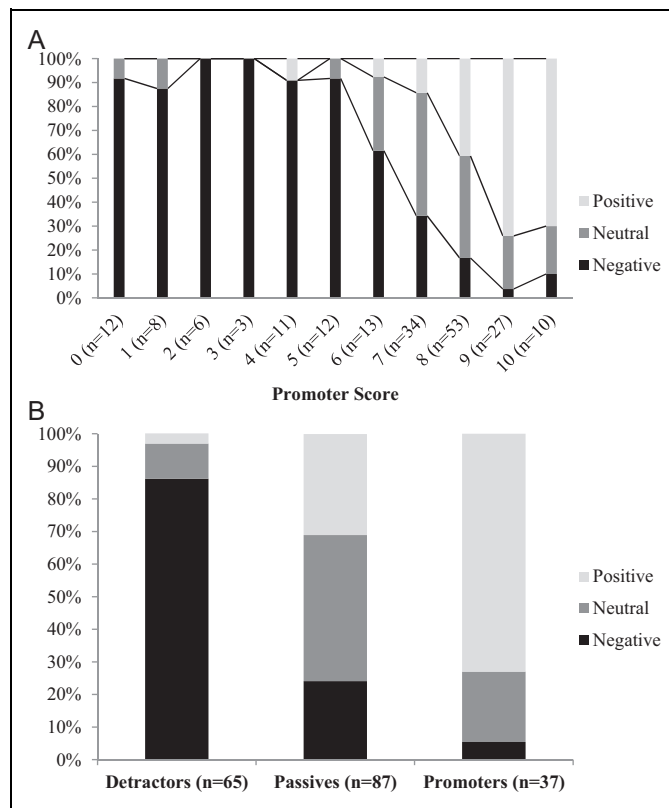


Figure 3. (A) Percentage of positive, neutral, and negative online word-of-mouth (eWOM) messages per promoter score ($n = 189$). (B) Percentage of positive, neutral, and negative eWOM messages per Net Promoter Score category ($n = 189$).

message valence is weaker for customers who leave more days between the NPS survey date and the occurrence of eWOM.

Additionally, an ANOVA was run to validate the findings regarding message valence homogeneity within NPS categories for the different time frames. We find that the results of these additional tests mimic the results of the main model.

Model With More Fine-Grained Measurement of Valence

In the main analysis, a 3-point scale (i.e., positive vs. neutral vs. negative) measures eWOM message valence. To assess the robustness of the findings to the subtlety of the message valence measurement, the model was estimated again using a more fine-grained measure of message valence, in particular, by extending the 3-point scale to a 5-point scale (in which 1 = *very negative* and 5 = *very positive*). In the first category (*very negative*), messages contain adjectives to strengthen the negative meaning, advice to avoid becoming a customer of the company, or explicit statements about leaving the company. In contrast, the fifth category (*very positive*) includes messages containing adjectives to strengthen the positive meaning, advice to become a customer of the company, or explicit statements about staying with the company.³ As with the original scale, we manually determined the valence of the customers' social media messages. Cohen's κ was sufficiently large (Neuendorf 2002), that is, 96% for Company 1 and 94% for Company 2, respectively. The results are robust to this alternative specification, except for the interaction effect between customers' promoter score and frequency, which becomes insignificant ($p > .10$). Further, we also reestimated the

Table 5. Results of Ordered Logit Analysis for eWOM Message Valence by Using 3-Month, 6-Month, and 1-Year Time Frames.^a

Variable	<3 Months ($n = 335$)	<6 Months ($n = 478$)	<1 Year ($N = 659$)
	Parameter Estimate	Parameter Estimate	Parameter Estimate
Intercept ^b			
Cut Point 1	-4.19*** (.92)	-3.57*** (.64)	-3.21*** (.53)
Cut Point 2	-6.57*** (.96)	-5.88*** (.68)	-5.61*** (.56)
Main effects			
Promoter score (PS)	.78*** (.12)	.70*** (.09)	.65*** (.07)
Recency	.00 (.00)	.00 (.00)	.00 (.00)
Frequency	-.25* (.21)	-.21* (.15)	-.02 (.11)
Interaction effects			
PS \times Recency	-.01*** (.00)	-.00** (.00)	-.00*** (.00)
PS \times Frequency	.16* (.13)	.17* (.09)	.09* (.07)
Control variable			
Company dummy	-.86*** (.24)	-.93*** (.20)	-1.05*** (.17)
-2 Log likelihood	549	822	1,157
χ^2 Likelihood ratio	168***	203***	239***
AIC	565	838	1,173
Concordance percentage	81.3	79.4	77.6
McFadden pseudo R^2	.23	.20	.17

Note. AIC = Akaike information criterion.

^aStandard errors are reported in parentheses. ^bCut Point 1 shows the logit for negative versus neutral valence, and Cut Point 2 shows the logit for negative versus positive valence. As we are able to reject the null hypothesis that the cut points are equal ($p_s < .01$), there seems no need to reduce the number of categories.

* $p < .10$. ** $p < .05$. *** $p < .01$.

ANOVA for validating the results regarding eWOM message valence homogeneity within and eWOM message valence heterogeneity across categories. The results remained substantively the same.

Resampling by Applying Cross Validation and Bootstrapping

We check sampling variability of the estimates by leave-one-out cross validation and by bootstrapping (1,000 subsamples). The average parameter estimates and their standard errors obtained by these resampling techniques are very close to the original estimates. Thus, we are confident about the stability of the parameters of interest and the robustness of our findings.

Conclusion and Discussion

Many of the largest companies including American Express, Microsoft, and Philips adopted the NPS. Practitioners use the NPS primarily as a summary statistic that has predictive value in determining a company's growth (Reichheld 2003). However, by using aggregate-level data, companies run the risk of falling into the trap of ecological fallacy. To what degree is it possible to draw conclusions on individual behavior based on group data? To answer this question, this study concentrates on the validity of the NPS and examines how individual customers' promoter scores are related to eWOM behavior, including its relationship with the NPS categories.

Firstly, the NPS concept assumes that the would recommend question is the single best gauge of customer behavior (Reichheld 2006). One might doubt this assumption by maintaining that only a portion of the customers who state that they will recommend the company to others actually do so. Thus, the would recommend question is an attitudinal measure and cannot be related to customers' actual behavior. As the relationship between recommendation and actual behavior should be established before one can aggregate the data, this research concentrates on the relationship between customers' individual promoter scores and eWOM behavior. Our results indicate that customers' promoter scores are significantly related to eWOM behavior. In particular, if a customer gives a high (low) promoter score and engages in eWOM behavior, this customer is more likely to spread positive (negative) eWOM. Further, the more messages a customer spreads online, the stronger the relationship between the customer's promoter score and eWOM message valence. Interestingly, customers are not only engaged in immediate WOM (i.e., spreading WOM messages about the company within the first month of the NPS survey date), but the company receives ongoing WOM over multiple months up to at least 1 year. It should be noted, however, that the larger the time lag between the NPS survey date and the date the message is online, the weaker the relationship between the promoter score and the valence of the online message. These findings extend research on customers' WOM behavioral intentions. Further, it contributes to the literature on the

NPS concept. In particular, the results show that the would recommend question is able to capture real or actual eWOM behavior (with respect to message valence). Thus, in line with the results of De Haan, Verhoef, and Wiesel (2015, p. 204), monitoring NPS does not seem to be wrong.

Secondly, the NPS concept assumes that promoters are the source of most of a company's positive WOM whereas detractors account for most negative WOM, without accounting for individual differences between customers. This leads to missed opportunities. Our results indicate that Reichheld's (2003) classification is partly justified. In particular, we find that detractors and promoters are homogeneous with respect to eWOM message valence. However, even though customers can be categorized as either detractors or promoters, and detractors mainly spread negative eWOM and promoters engage mostly in positive eWOM behavior, the aggregated data might still lead to difficulties in understanding individual differences between customers within one of these groups. The results further show that passives are heterogeneous with respect to eWOM message valence. As expected, passives are different from both detractors and promoters, but, counter to expectations, customers who award the company with a promoter score of 7 differ from customers who award the company with a score of 8 when the valence of the online messages is considered. While it is assumed that the group of passively satisfied customers did not experience major problems with the company and represents therefore the easiest group to move upward (Goodman and Gonier 2011), our results show that making such generalizations is a risky strategy. Thus, whereas previous research shows that assigning customers as detractors, passives, or promoters and focusing on the extremes (i.e., detractors and promoters) is preferable to using the full scale (De Haan, Verhoef, and Wiesel 2015), our findings urge the need for focusing on the full scale when examining eWOM message valence.

Interestingly, it appears that customers in our sample have the tendency to spread more negative than positive eWOM, which differs from previous research that indicates that customers give more positive than negative WOM (East, Hammond, and Wright 2007). While the literature is inconclusive about the relative impact of positive and negative WOM (e.g., East, Hammond, and Lomax 2008), research shows that positive WOM generates sales, awareness, and loyalty, whereas negative WOM is detrimental for achieving these goals (Luo 2009). Further, negative messages tend to diffuse at a faster rate than positive messages (Allsop, Bassett, and Hoskins 2007).

Managerial Implications

Currently, companies have the tendency to fixate on their NPS score and assume that there is a direct value in the NPS. We argue, however, that an in-depth and nuanced understanding of the NPS is relevant for managers. Indeed, while our results do not seem to be inconsistent with using the NPS as a measure of how well the company is doing, they simultaneously imply that

by examining the available data more closely, beyond evaluation, the data can provide diagnostics and normative implications. In particular, we urge managers to pay attention to the relative number of customers in each of the NPS groups and consider the whole distribution of promoter scores, rather than just the percentage of customers in each of the three groups. Indeed, NPS is a means to an end, rather than an end in itself. Key should be to close the loop with customers and to take appropriate action. When a customer provides feedback in the form of a promoter score and eWOM, it provides the company an opportunity to engage and deepen its connection with this customer. Understanding how customers communicate their experiences with a company (i.e., eWOM message valence and its recency and frequency) is important inasmuch as eWOM reflects service quality and customer satisfaction and is at the same time a precursor to sales and profits (Duan, Gu, and Whinston 2008; Wangenheim and Bayón 2007). As eWOM is hard to influence (Van Noort and Willemsen 2012), the goal of the company should not be to manipulate eWOM. Rather, companies should effectively manage the information that is available (i.e., the individual customers' promoter scores and their corresponding eWOM behavior—valence, recency, and frequency) and act upon this knowledge appropriately. Important in this regard is that companies should not incorrectly assume aggregated-level features or behaviors to apply at the individual level (e.g., all promoters are spreading positive eWOM, whereas all detractors engage in negative eWOM). On the contrary, managers should pay attention to the whole distribution of promoter scores.

Further, the online messages spread by passives provide a rich data source for managers as well. To exemplify, we focus on the strength of the recommendations. While detractors are prevalently very negative, writing messages such as, "Again a technical failure from Company 2, so no telephone or Internet. This really \$@#@", 27% of the negative eWOM messages come from passively satisfied customers, who according to the classification of Reichheld (2003) should be neutral. These negative eWOM messages are as negative as the messages spread by the detractor group. For example, one customer who rated the company with a promoter score of 7 wrote "Just treated very rudely by company 2, absolutely absurd. I will end my contract for sure." Interestingly, almost 50% of the positive eWOM messages come from passively satisfied customers (mainly from customers who award the company an 8). We can conclude that the strength of the positive messages spread by the passives do not differ substantially from those spread by promoters. To exemplify, a customer who provided the company with a promoter score of 8 stated, "I had a flat tire and called Company 1. They helped me on the road within 15 minutes, really top service."

As is evident, while passives are assumed to be neutral, they are responsible for a substantial part of the online messages with either a negative or positive valence. Nevertheless, in practice, passives, which form the majority, have no weight in calculating the NPS. The NPS concept focuses on the percentage of customers in the promoter group versus the

percentage of customers in the detractor group. Passives are often viewed as somewhat satisfied or even satisfied (as opposed to very satisfied) and receive a low-priority status (Goodman and Gonier 2011). Indeed, companies are often inclined to focus on either the promoters or detractors, while ignoring the passives. On the contrary, we suggest that managers should not ignore passives and do not perceive passively satisfied customers as a homogeneous group. Rather, they should consider individual customers' responses and follow-up to passively satisfied customers. In particular, they should look at what eWOM passives are actually spreading, flag them for further attention and action by customer service, and act accordingly. We speculate that web (or social media) monitoring and webcare are useful tools in this regard. Whereas web monitoring enables companies to make collective sense of the short, speedy, and numerous conversations on social media (Kietzmann et al. 2011), webcare allows companies to engage in online interactions with (complaining) customers by actively searching the web to address customer feedback such as questions, concerns, and complaints (Van Noort and Willemsen 2012).

Limitations and Suggestions for Further Research

This study has several limitations, some of which provide worthwhile avenues for further research. First, we examined the relationship between customers' promoter scores and eWOM behavior. Because NPS is tied to company growth, future investigations could enhance our research by examining the consequences of eWOM, such as sales and retention. In addition, while our findings suggest that higher promoter scores correspond with positive eWOM behavior and vice versa, managers should realize that promoters do not always produce positive eWOM and detractors do not always engage in negative eWOM (cf. East, Hammond, and Wright 2007). Thus, while the NPS provides companies with valuable information on broad customer populations, that is, promoters and detractors, it provides little insights into individual customer motivations to spread either positive or negative eWOM. Future research could model the drivers of eWOM to shed light on how companies can generate eWOM success, that is, amplify positive and mitigate negative eWOM.

In addition to the drivers and consequences of eWOM, future research could enrich our analyses by incorporating data on customer experiences and service delivery. Relevant variables include the nature of the service that led to asking the NPS question (e.g., order, purchase, complaint), service interface (e.g., personal, technology based), and the valence of the customer experience. Additionally, other (service) events taking place between the NPS survey date and the occurrence of eWOM should be accounted for as these events might influence the promoter score or eWOM message valence. In fact, we encourage researchers to take a dynamic approach and model the change in customers' promoter scores and eWOM message valence.

Secondly, it was not possible to retrieve information on customers who did not engage in eWOM but provided a promoter score (despite being active on social media). As such, our data consist only of customers who provided both a promoter score and engaged in eWOM behavior on the two companies that participated in our study. Because this may create a selection bias, we encourage scholars to investigate the nonreferral phenomenon by modeling a two-step process: firstly, whether an eWOM referral is made, and secondly, given that a customer engages in eWOM, its valence, recency, and frequency. Further, due to privacy reasons, information on customer characteristics could not be attained. Demographic or psychographic information could be used by future research to identify segments that have substantial impact on the companies' NPSs. This information could also be used to examine the composition of the categories as defined by Reichheld (2003). Additionally, experiential demographics (e.g., data related to the phases of the customer life cycle) could provide valuable insights into the NPS. For example, to which category do repeat or loyal customers belong? Are new customers using the NPS scale differently to repeat customers? Combining data on the NPS and the customer life cycle is a fruitful area for future research.

Thirdly, eWOM may not be representative for overall WOM (Lovett, Peres, and Shachar 2013; Trusov, Bucklin, and Pauwels 2009). While with the advent of social media eWOM behavior becomes increasingly important and even though our operationalization of customers' actual behavior is in line with Godes and Mayzlin's (2004) finding that online conversations can offer an easy and cost-effective way to measure WOM, it would be useful to replicate our findings for off-line measurements of WOM.

Finally, our sample only consists of customers who respond to the NPS survey. Consequently, it might be that only current customers are included in our sample. Future research could take into account past customers who are still engaged in eWOM behavior and explore (behavioral) differences between current and past customers. Additionally, we face nonresponse bias. Customers who are more motivated to take the time to answer the NPS survey are more likely to have had a very good or very bad experience with the company but are not necessarily representative of the customer population. While this bias might help the NPS to make better predictions, future research might address the question whether promoters, passives, and detractors who respond to the NPS survey differ from customers who did not respond and, more importantly, in what way they differ.

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Notes

1. In this article, we refer to promoter scores as the individual customers' responses to the promoter question, while the company's Net Promoter Score reflects the company-level summary of the percentage of promoters minus the percentage of detractors.
2. Another relevant question, which should actually precede our focal questions, is whether an online word-of-mouth referral is made if a customer provided a promoter score. However, due to data access limitations, we were only able to retrieve data on customers who both provide a promoter score and engaged in eWOM, which makes us unable to study the nonreferral phenomenon.
3. One could also make a distinction between message valence (i.e., positive, neutral, or negative) and actual recommendation or discouragement behavior. Indeed, it is not clear that positive (negative) eWOM is the same as actually recommending (advising against) a company to someone else. Unfortunately, our sample contains too less messages concerning actual recommendation and discouragement behavior ($n < 10$) to make empirical generalizations about this distinction.

References

- Allsop, Dee T., Bryce R. Bassett, and James A. Hoskins (2007), "Word-of-Mouth Research: Principles and Applications," *Journal of Advertising Research*, 47 (4), 398-411.
- Beckers, Sander F. M., Hans Risselada, and Peter C. Verhoef (2014), "Customer Engagement: A New Frontier in Customer Value Management," in *Handbook of Service Marketing Research*, Roland T. Rust and Ming-Hui Huang, eds. Cheltenham, UK: Edward Elgar, 97-120.
- Brown, Tom J., Thomas E. Barry, Peter A. Dacin, and Richard F. Gunst (2005), "Spreading the Word: Investigating Antecedents of Consumers' Positive Word-of-Mouth Intentions and Behaviors in a Retailing Context," *Journal of the Academy of Marketing Science*, 33 (2), 123-138.
- Bulik, Beth Snyder (2013), "How Jiffy Lube Used its Net Promoter Score to Goose Sales," (accessed November 21, 2016), [available at <http://adage.com/article/dataworks/jiffy-lube-net-promoter-score-goose-sales/243046/>].
- Burnham, Kenneth P. and David R. Anderson (2002), *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*. New York, NY: Springer-Verlag.
- Chandon, Pierre, Vicki G. Morwitz, and Werner J. Reinartz (2005), "Do Intentions Really Predict Behavior? Self-Generated Validity Effects in Survey Research," *Journal of Marketing*, 69 (2), 1-14.
- Chen, Yubo and Jinhong Xie (2008), "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix," *Management Science*, 54 (3), 477-491.

- Cummings, Jonathon N. (2004), "Work Groups, Structural Diversity, and Knowledge Sharing in a Global Organization," *Management Science*, 50 (3), 352-364.
- De Haan, Evert, Peter C. Verhoef, and Thorsten Wiesel (2015), "The Predictive Ability of Different Customer Feedback Metrics for Retention," *International Journal of Research in Marketing*, 32 (2), 195-206.
- De Matos, Celso Augusto and Carlos Alberto Vargas Rossi (2008), "Word-of-Mouth Communications in Marketing: A Meta-Analytic Review of the Antecedents and Moderators," *Journal of the Academy of Marketing Science*, 36 (4), 578-596.
- Dellarocas, Chrysanthos (2003), "The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms," *Management Science*, 49 (10), 1407-1424.
- Duan, Wenjing, Bin Gu, and Andrew B. Whinston (2008), "The Dynamics of Online Word-of-Mouth and Product Sales—An Empirical Investigation of the Movie Industry," *Journal of Retailing*, 84 (2), 233-242.
- East, Robert, Kathy Hammond, and Wendy Lomax (2008), "Measuring the Impact of Positive and Negative Word of Mouth on Brand Purchase Probability," *International Journal of Research in Marketing*, 25 (3), 215-224.
- East, Robert, Kathy Hammond, and Malcolm Wright (2007), "The Relative Incidence of Positive and Negative Word of Mouth: A Multi-Category Study," *International Journal of Research in Marketing*, 24 (2), 175-184.
- Forbes (2011), "The 'Relative NPS' Trap: Why Philips Isn't Delighting Its Customers," (accessed August 25, 2016), [available at <http://www.forbes.com/sites/stevedenning/2011/11/02/the-relative-nps-trap-why-philips-isnt-delighting-its-customers/>]
- Gelbrich, Katja, Jana Gäthke, and Yany Grégoire (2015), "How Much Compensation Should a Firm Offer for a Flawed Service? An Examination of the Nonlinear Effects of Compensation on Satisfaction," *Journal of Service Research*, 18 (1), 107-123.
- Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545-560.
- Goodman, John and Dennis Gonier (2011), "The Passives Are Not Passive: Why You Should Be Careful with the Net Promoter Score," *Quirk's Marketing Research Review*, 25 (10), 72-78.
- Green, Sandy Edward Jr., Yuan Li, and Nitin Nohria (2009), "Suspended in Self-Spun Webs of Significance: A Rhetorical Model of Institutionalization and Institutionally Embedded Agency," *Academy of Management Journal*, 52 (1), 11-36.
- Grossman, Randi P. and Brian D. Till (1998), "The Persistence of Classically Conditioned Brand Attitudes," *Journal of Advertising*, 27 (1), 23-31.
- Gupta, Sunil and Valarie Zeithaml (2006), "Customer Metrics and Their Impact on Financial Performance," *Marketing Science*, 25 (6), 718-739.
- Harrison-Walker, L. Jean (2001), "The Measurement of Word-of-Mouth Communication and an Investigation of Service Quality and Customer Commitment as Potential Antecedents," *Journal of Service Research*, 4 (1), 60-75.
- Hennig-Thurau, Thorsten, Kevin P. Gwinner, Gianfranco Walsh, and Dwayne D. Gremler (2004), "Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet?" *Journal of Interactive Marketing*, 18 (1), 38-52.
- Keiningham, Timothy L., Lerzan Aksoy, Bruce Cooil, and Tor Wallin Andreassen (2008a), "Linking Customer Loyalty to Growth," *MIT Sloan Management Review*, 49 (4), 51-57.
- Keiningham, Timothy L., Lerzan Aksoy, Bruce Cooil, Tor Wallin Andreassen, and Luke Williams (2008b), "A Holistic Examination of Net Promoter," *Database Marketing & Customer Strategy Management*, 15 (2), 79-90.
- Keiningham, Timothy L., Lerzan Aksoy, Arne de Keyser, Bart Larivière, Alexander Buoye, and Luke Williams (2014), "It's Not Your Score that Matters: The Importance of Relative Metrics," in *Handbook of Service Marketing Research*, Roland T. Rust and Ming-Hui Huang, eds. Cheltenham, UK: Edward Elgar, 166-181.
- Keiningham, Timothy L., Bruce Cooil, Tor Wallin Andreassen, and Lerzan Aksoy (2007), "A Longitudinal Examination of Net Promoter and Firm Revenue Growth," *Journal of Marketing*, 71 (3), 39-51.
- Keller, Kevin L. (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (1), 1-22.
- Kietzmann, Jan H., Kristopher Hermkens, Ian P. McCarthy, and Bruno S. Silvestre (2011), "Social Media? Get Serious! Understanding the Functional Building Blocks of Social Media," *Business Horizons*, 54 (3), 241-251.
- Kozinets, Robert V., Kristine de Valck, Andrea C. Wojnicki, and Sarah J. S. Wilner (2010), "Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities," *Journal of Marketing*, 74 (2), 71-89.
- Kristensen, Kai and Jacob Eskildsen (2014), "Is the NPS a Trustworthy Performance Measure?" *The TQM Journal*, 26 (2), 202-214.
- Kumar, V., J. Andrew Petersen, and Robert P. Leone (2010), "Driving Profitability by Encouraging Customer Referrals: Who, When, and How," *Journal of Marketing*, 74 (5), 1-17.
- Kumar, V., J. Andrew Petersen, and Robert P. Leone (2007), "How Valuable Is Word of Mouth?" *Harvard Business Review*, 85 (10), 139-146.
- Kumar, V., Ilaria Dalla Pozza, and Jaishankar Ganesh (2013), "Revisiting the Satisfaction-Loyalty Relationship: Empirical Generalizations and Directions for Future Research," *Journal of Retailing*, 89 (3), 246-262.
- Lovett, Mitchell J., Renana Peres, and Ron Shachar (2013), "On Brands and Word of Mouth," *Journal of Marketing Research*, 50 (4), 427-444.
- Luo, Xueming (2009), "Quantifying the Long-Term Impact of Negative Word of Mouth on Cash Flows and Stock Prices," *Marketing Science*, 28 (1), 148-165.
- Mackintosh, Darren (2015), "Net Promoter Scores: Monitoring Practice Performance," *In Practice*, 37 (7), 370-372.
- Morgan, Neil A. and Lopo Leotte Rego (2006), "The Value of Different Customer Satisfaction and Loyalty Metrics in Predicting Business Performance," *Marketing Science*, 25 (5), 426-439.

- Neuendorf, Kimberly A. (2002), *The Content Analysis Guidebook*. Thousand Oaks, CA: Sage.
- Ranaweera, Chatura and Chanaka Jayawardhena (2014), "Talk Up or Criticize? Customer Responses to WOM about Competitors during Social Interactions," *Journal of Business Research*, 67 (12), 2645-2656.
- Reichheld, Frederick F. (2006), "The Microeconomics of Customer Relationships," *MIT Sloan Management Review*, 47 (2), 73-78.
- Reichheld, Frederick F. (2003), "The One Number You Need to Grow," *Harvard Business Review*, 81 (12), 46-54.
- Reichheld, Frederick F. and Rob Markey (2011), *The Ultimate Question 2.0: How Net Promoter Companies Thrive in a Customer-Driven World*. Boston, MA: Harvard Business Review Press.
- Rust, Roland T., Valarie A. Zeithaml, and Katherine N. Lemon (2000), *Driving Customer Equity: How Customer Lifetime Value Is Reshaping Corporate Strategy*. New York, NY: Free Press.
- Santoro, Michael D. and Joseph P. McGill (2005), "The Effect of Uncertainty and Asset Co-Specialization on Governance in Biotechnology Alliances," *Strategic Management Journal*, 26 (13), 1261-1269.
- Sheeran, Paschal (2002), "Intention-Behavior Relations: A Conceptual and Empirical Review," *European Review of Social Psychology*, 12 (1), 1-36.
- StatisticBrain.com (2015), "Social Networking Statistics," (accessed February 22, 2016), [available at <http://www.statisticbrain.com/social-networking-statistics/>.]
- Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing*, 73 (5), 90-102.
- Van Doorn, Jenny, Peter S. H. Leeflang, and Marleen Tijs (2013), "Satisfaction as a Predictor of Future Performance: A Replication," *International Journal of Research in Marketing*, 30 (3), 314-318.
- Van Noort, Guda and Lotte M. Willemsen (2012), "Online Damage Control: The Effects of Proactive versus Reactive Webcare Interventions in Consumer-Generated and Brand-Generated Platforms," *Journal of Interactive Marketing*, 26 (3), 131-140.
- Wangenheim, Florian V. and Tomás Bayón (2007), "The Chain from Customer Satisfaction via Word-of-Mouth Referrals to New Customer Acquisition," *Journal of the Academy of Marketing Science*, 35 (2), 233-249.

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